

MEASURING SOCIOECONOMIC INEQUALITY IN OBESITY: LOOKING BEYOND THE OBESITY THRESHOLD

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ABSTRACT

We combine two of the most widely used measures in the inequality and poverty literature, the concentration index and Foster–Greer–Thorbecke metric to the analysis of socioeconomic inequality in obesity. This enables us to describe socioeconomic inequality not only in obesity status but also in its depth and severity. We apply our method to 1971–2012 US data and show that while the socioeconomic inequality in obesity status has now almost disappeared, this is not the case when depth and severity of obesity are considered. Such socioeconomic gradient is found to be greatest among non-Hispanic whites, but decomposition analysis also reveals an inverse relationship between income and obesity outcomes among Mexican Americans once the effect of immigrant status has been accounted for. The socioeconomic gradient is also greater among women with marital status further increasing it for severity of obesity while the opposite is true among men. Overall, the socioeconomic gradient exists as poorer individuals lie further away from the obesity threshold. Our study stresses the need for policies that jointly consider obesity and income to support those who suffer from the double burden of poverty and obesity-related health conditions. © 2016 The Authors. *Health Economics* Published by John Wiley & Sons Ltd.

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1. INTRODUCTION

One of the most prominent global public health concerns is the growing prevalence of overweight and obesity. The increase in obesity rates in developed and developing countries has been described as a global epidemic (WHO 2000). More recent evidence shows that childhood overweight rates are plateauing internationally, which might in turn affect future trends in adult obesity (Olds et al. 2011). In the United States, approximately one third of adults are currently classified as obese and two-thirds as overweight (Ogden et al. 2012). Obesity is associated with several diseases, including cardiovascular diseases, diabetes, and some cancers (WHO 2000), and its direct and indirect costs are estimated at greater than \$140bn annually in the United States alone (Finkelstein et al. 2009; Cawley and Meyerhoefer 2012). The processes that influence excess adiposity are complex and involve numerous factors, including genetic predisposition, behavioral, environmental, social, and cultural dynamics.

A major concern in rich countries is that obesity might disproportionately affect individuals with low socioeconomic status (SES) as this could further deteriorate the socioeconomic gradient in health. In order to estimate the relationship between SES and excess adiposity, many studies have used linear regressions with BMI as a dependent variable and/or logistic regressions explaining obesity status (i.e., whether BMI is greater

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or equal to 30 or not). For example, using National Health and Nutrition Examination Survey (NHANES) data with family income as a measure of SES Chang and Lauderdale (2005) found that, over the 1999–2002 period, white women had a strong inverse obesity/income gradient and that there was a significant difference between the poorest and highest income quartile for white men and black women. On the other hand, the authors found a positive gradient for black and Mexican American men, and no statistically significant differences in obesity prevalence between income categories for Mexican American women. Over the 1971–2002 period, the authors found that while obesity had been increasing at all levels of income, the increase was less marked among the poor, and as a result, socioeconomic disparities have narrowed. Substantial differences between race and gender groups and reductions in socioeconomic disparities in obesity over time have also been found by Zhang and Wang (2004) with NHANES data for the same period but with education as a measure of SES, as well as by Singh *et al.* (2011) for immigrant populations using data from the 1976–2008 National Health Interview Surveys with income, education, and occupation as indicators of SES.

A limitation of the aforementioned analyses is that the logistic regressions focus on the obesity cut-off point and ignore differences beyond this point. Properly accounting for the long-right tail in the BMI distribution is essential to accurately evaluate the cost of the epidemic and choose appropriate targets for public policies (Andrejeva *et al.* 2007; Ruhm 2007). As for the linear regressions, they capture the average effect that SES has on BMI but ignore that income may affect weight differently along the BMI distribution. This latter issue was illustrated by Jolliffe (2011) who applied unconditional quantile regression to 1971–2006 NHANES data and showed that the linear regression underestimates the negative relationship between income and BMI when measured at the obesity threshold.

An alternative approach to regression analysis is the use of statistical indices. Jolliffe (2011) applied the distribution-sensitive Foster–Greer–Thorbecke (FGT) indices (Foster *et al.* 1984) to measure the prevalence, depth, and severity of obesity, where depth is defined as the average excess BMI over the obesity threshold and severity as the average squared excess. An important advantage of the latter two indices is that they account for how far obese individuals lie above the threshold. As highlighted by Jolliffe (2004), application of the FGT indices to excess weight addresses two shortcomings associated the prevalence measure. First, when overweight is measured as a dichotomous outcome, too much emphasis is placed on the selected threshold. Second, the prevalence method is insensitive to changing BMI distribution beyond the threshold; therefore, it is unaffected by an obese person gaining or losing weight. Similar reasons have led Madden (2012) to analyze potential stochastic dominance between BMI distributions and to derive a decomposition of a measure similar to the FGT measure of depth according to changes in contributing factors over time. A limitation of the FGT indices, although, is that they do not directly provide a measure of the socioeconomic gradient in obesity; it would need to be separately computed over income categories. This can require a large sample size to reveal differences that are statistically significant and, more importantly, does not make it possible to control for, or analyze, the effect of additional factors on obesity such as gender, race, and birthplace.

A more direct approach is to summarize the socioeconomic gradient by means of the concentration index (CI hereafter, Kakwani 1977), which is a standardized measure of socioeconomic inequality. Applying the CI to 1988–1994 NHANES data, Zhang and Wang (2004) found that the inverse association between SES and obesity status is stronger for women than men and weaker in minority groups. Further, Costa-Font and Gil (2008) exploited another advantage of the CI, which is that it can be decomposed according to factors that are both associated with SES and obesity. Using data from the 2003 Spanish National Health Survey, the authors showed that a significant part of the income-related inequality in obesity status that was observed in Spain was associated with education and demographic variables.

It is important to stress, however, that previous applications of the CI to the study of obesity suffer from a similar limitation to that of the logistic regression mentioned previously, namely that they ignore the BMI distribution above the obesity threshold. To extend prior analyses, we combine two of the most widely used measures in the inequality and poverty literatures: the CI and FGT metric and apply them to gain further insights into the relationship between status, depth, and severity of obesity and SES. We then decompose these FGT-CIs by means of a two-part model (TPM hereafter, Duan *et al.* 1983 to identify which factors are

associated with overall socioeconomic inequality. Therefore, our method combines the synthesis power of the CI with that of regression analysis. This allows us to further decompose the contribution of each factor to the overall socioeconomic inequality into the association of each factor with the obesity measure (obtained from the regression) and its distribution according to SES (computed with factor-specific CIs).

We apply our method to 1971–2012 NHANES data and notably show that while the negative socioeconomic inequality in obesity status has now almost disappeared, this is not the case when depth and severity of obesity are considered as poorer obese individuals have more severe obesity compared with their richer compatriots. We also measure the respective contribution of age, gender, race, immigration, marital status, family income, and education to socioeconomic inequality and provide race-specific and gender-specific analyses given the importance of these two factors in the literature.

2. METHODS

Our objective is to measure and analyze socioeconomic inequality in the distribution of obesity. An important distinction from earlier work of Zhang and Wang (2004) is that we do not restrict the analysis to obesity status (i.e., obese vs non-obese) and also account for the distribution of BMI above the obesity threshold. To do so, we define obesity measures along the lines of the FGT distribution-sensitive indices (1984):

$$Y = \begin{cases} (BMI - c)^\alpha & \text{if } BMI \geq c \\ 0 & \text{otherwise} \end{cases},$$

where c is the obesity threshold, and α is a parameter that sets the sensitivity of the measure to deviations above the obesity threshold. When $\alpha=0$, Y indicates whether the individual is obese or not and yields a measure of obesity ‘status’. When $\alpha=1$, Y measures how far the BMI of obese individuals lies above the obesity threshold and yields a measure of ‘depth’ of obesity. Finally, when $\alpha=2$, Y increases quadratically above the obesity threshold and is interpreted as a measure of ‘severity’ of obesity. Unlike FGT, we are not interested in the average of the above measures but in their distribution according to SES.

The aforementioned measures provide three complementary perspectives on the relationship between income and BMI. It is possible to give additional interpretations to these measures in terms of concentration of obesity-related health burden by accounting for the relationship between excess health burden, $(h_c - h_{BMI})$, and excess BMI, $(BMI - c)$:

$$h_c - h_{BMI} = \beta(BMI - c)^\alpha, \text{ if } BMI \geq c,$$

where h_c and h_{BMI} represent individual health status at the obesity threshold and for any BMI above the threshold, respectively; α is the FGT power, and β is a constant without incidence on measurement as the CI is a relative measure of inequality. It is then possible to calculate the FGT power by taking the log of each side of the equation and estimating α via ordinary least squares (OLS):

$$\log(h_c - h_{BMI}) = \log\beta + \alpha\log(BMI - c), \text{ if } BMI \geq c.$$

By way of example, using published aggregate data on excess mortality rates (above an ideal BMI) as a function of BMI categories (Prospective Studies Collaboration 2009), we estimated α at 1.05 (95% CI: 0.82; 1.27). This indicates a roughly linear relationship between excess mortality and excess BMI (results available upon request). Similarly, the results published by Fontaine *et al.* (2003) suggest a linear relationship between years of life lost due to obesity and BMI. Consequently, the CI of depth of obesity can also be interpreted as the distribution (according to income) of excess mortality that is associated with obesity. Results from several studies conducted in the United States (Jia and Lubetkin 2005; Sach *et al.* 2007; Finkelstein *et al.* 2010) indicate that health-related quality of life decreases approximately quadratically with BMI above the obesity threshold. Thus, the CI of severity of obesity can also be thought of as approximately reflecting the distribution (according to income) of quality of life lost due to obesity.

We quantify the socioeconomic inequality in the distribution of the above obesity measures by means of the CI (Kakwani 1977), which measures the size of inequalities in any positive quantitative variable of interest between the poor and better off. It is calculated similarly to the well-known Gini index of income inequality with the only difference being that it relates the concentration of another variable, often a disease burden variable, to the cumulative rank of the income distribution. The CI is standardized between -1 and $+1$, which makes it possible to compare the direction and magnitude of socioeconomic inequality through time, between populations and even between different variables. This index has been applied to measure and compare the socioeconomic inequality in a large number of health-related variables including obesity status (see for instance O'Donnell and Wagstaff 2008, for an extensive discussion). When applied to obesity, negative CIs indicate that the burden of obesity is disproportionately borne by lower income individuals whereas positive values indicate that richer individuals are more affected. Computing separate FGT-CIs for status, depth, and severity of obesity makes it possible to compare socioeconomic inequality with respect to these three different aspects of obesity. Note that the CI for obesity status is only affected by the rank in the income distribution of those individuals that exceed the obesity threshold but not by the extent to which the threshold is exceeded. The CIs for depth and severity are sensitive to both the rank in the income distribution and excess BMI above the obesity threshold. The difference between the two CIs can be illustrated by considering two equally poor individuals in a given sample. The CI for depth would be identical in the following two cases: (i) the two individuals are obese, and both are 1 BMI point above the obesity threshold; and (ii) one of them is not obese, and the other exceeds the obesity threshold by 2 BMI points. The CI for severity would show a greater obesity burden for the poor in the second case as a poor individual falls further away from the obesity threshold.

Further insight can be gained by decomposing the CI into the contributions made by factors that are correlated with both obesity and income. For instance, if both BMI and income increase with age, part of the measured socioeconomic inequality in obesity can be associated with age. Wagstaff *et al.* (2003) showed that such decomposition can be obtained when the variable of interest is expressed as a linear model of the contributing factors. It is important to stress, however, that modeling the above FGT measures is intrinsically a nonlinear exercise as, by definition, these measures comprise a potentially large proportion of observations with zero value (i.e., the non-obese), and positive values are generally right-skewed for depth and severity. To address these characteristics, we apply TPMs, which have been widely used in health econometrics, especially in the modeling of health care expenditure data (see Jones 2012, for a review). TPMs are adequate for FGT measures as the zero values taken by these measures are 'true zeros' in the sense that values that lie below the threshold do not contribute to the FGT measures. In the context of obesity, BMI values that lie below the obesity threshold do not count toward the obesity burden, and their contribution to the FGT measure are true zeros. Note that these zeros should not be confused with censoring. In the case of censoring, the values that fall below the threshold are of interest to the analyst but are not observed.

Regarding the specification of the first part of the TPM, we apply a Logit model, which is a standard choice both for TPMs and modeling the probability of being obese. For the second part, we opted for a generalized linear model (GLM, Nelder and Wedderburn 1972) as this family offers many alternatives to the linear model that are suitable to skewed data. We used the Box–Cox (Box and Cox 1964) and Park (Park pre-1986; Manning and Mullahy 2001) tests to determine the GLM link function and distribution family. In our analysis, these tests support the use of a log-Gamma GLM for both depth and severity of obesity.

Because TPMs are nonlinear, we use the Doorslaer *et al.* (2004) approximation of the Wagstaff *et al.* (2003) decomposition of the CI:

$$CI_Y = \sum_{k=1}^K \frac{\partial \bar{E}(Y|X)}{\partial X_k} \frac{\bar{x}_k}{\mu} CI_k + GC_\varepsilon,$$

where CI_Y and CI_k represent the CI of the FGT variable Y and factor x_k , respectively; μ and \bar{x}_k , the sample average of Y and factor x_k ; $\partial \bar{E}(Y|X)/\partial X_k$, the average marginal effect of factor x_k on Y obtained from the TPM estimates; and remainder GC_ε , the generalized CI of the regression residuals. Note that marginal effects in

TPMs, as with all nonlinear models, depend upon where they are evaluated. To avoid choosing an arbitrary evaluation point, we first computed the marginal effects for each respondent and averaged these over the sample analyzed. In the decomposition, the contribution of each factor x_k equals the product of the elasticity of the FGT variable according to income, $\partial \bar{E}(Y|X)/\partial X_k \cdot \bar{x}_k/\mu$, and the socioeconomic inequality in the distribution of the factor, CI_k . The overall contribution to the FGT-CI of a categorical variable is obtained by summing the contribution of the binary variable associated to each category but the reference. In summary, to have an impact on the FGT-CI, CI_Y , a given factor x_k both needs to be correlated with Y as measured by its elasticity with Y and be unequally distributed according to income as measured by CI_k .

Finally, it is worth mentioning that the decomposition of the FGT-CI includes that of the standard CI for a continuous outcome as a special case when $c=0$ and $\alpha=1$, and where the TPM reduces to its second part only. With minor changes, the method also straightforwardly handles the case of upper censoring when the values of interest lie below a certain cut-off (e.g., BMI < 18.5 for the study of underweight). We programmed our method in STATA (version 13.1) as a standalone command (FGT_CI.ado, freely available) where we made use of the user-written commands twopm.ado (Belotti et al. 2015) to estimate the TPM and concind.ado (Chen 2007) to calculate CIs that adequately handle individuals with equal income.

3. STUDY SAMPLE AND VARIABLES

Our analysis is based on data from the NHANES conducted by the Centers for Disease Control and Prevention (CDC). NHANES is a multi-stage representative sample of the US civilian, non-institutionalized population. We separately analyze data from five time periods: 1971–1974 (NHANES I), 1976–1980 (NHANES II), 1988–1994 (NHANES III), 1999–2006, and 2007–2012 each obtained by combining 6 years of the continuous NHANES. The present study analyzes 56,194 adults aged 20 to 65 years with complete data on relevant anthropometric and socio-demographic characteristics (NHANES I: 9,756 observations; NHANES II: 9,121; NHANES III: 12,733; NHANES 1999–2006: 12,419; NHANES 2007–2012: 12,165). In continuous NHANES 1999–2012, 3,320 observations (14%) were removed from analysis because of missing values. The 8% of the sample had missing PIR data, and 5.6% had missing BMI. None were missing age, gender, or race, and a negligible number were missing other variables (location of birth, education, and marital status). In the first three NHANES, approximately 13% had missing PIR, and 3% had missing BMI. NHANES utilizes a complex, multistage probability sampling design, with oversampling of certain subgroups. All our analyses account for the survey design in order to produce nationally representative estimates and valid (bootstrapped) standard errors.

Respondents' body weight and height were measured by trained health professionals following standardized protocols with calibrated equipment. We used this information to calculate the respondents' BMI, which is a simple weight-for-height index that is commonly used to classify obesity in adults. It is defined as a person's weight in kilograms divided by the square of her height in meters (kg/m^2). As CDC classifies as obese those with a BMI exceeding 30 (NHLBI Obesity Education Initiative 1998), we computed all our FGT measures of obesity with respect to this threshold.

As a measure of income, we use the poverty income ratio (PIR), which is calculated by dividing family income by the poverty lines established by the federal register each year (Centers for Disease Control and Prevention (CDC) 2011). Poverty lines are updated yearly to account for inflation, vary by family size and composition, and use income before taxes as basis of calculation. PIR thus expresses the respondents' family income relative to a similar family whose income is exactly at the poverty line. The advantage of PIR is that it equalizes the respondents' income according to the size and composition of their family.

For the decomposition analyses of the FGT-CIs of obesity, we use age, gender, education level (less than 9th grade, high school no diploma, high school graduate, some college, or college graduate), marital status (married, divorced, widow, separated, living with partner, or single), immigrant status (born outside the United States or not), and race/ethnicity. Respondents self-identified as Mexican Hispanic, Hispanic, non-Hispanic white (white), non-Hispanic black (black), or as belonging to another race/ethnicity. Due to changes in survey

design over time and the small sample sizes for Hispanics and other races, reliable sub-sample estimates are only available for whites, blacks, and Mexican Hispanics. Table I presents summary statistics for the FGT obesity measures and individual characteristics for each NHANES survey.

4. RESULTS

4.1. Trend in socioeconomic inequality in obesity

Figure 1 displays the trend in socioeconomic inequality in status, depth, and severity of obesity across the years for which NHANES data were collected. We find that all FGT-CIs are negative and statistically significant, which reveals that obesity is more concentrated among the poor in the United States. Socioeconomic inequality in obesity is largest when using the severity measure and smallest when using the status measure. Figure 1 shows that all the measures of socioeconomic inequality in obesity have sharply decreased over the period analyzed. For instance, between the 1971–1974 and 2007–2012 periods, the FGT-CIs decreased from -0.162 to -0.028 for status, from -0.242 to -0.078 for depth, and from -0.315 to -0.119 for severity. Based on status measures only, it appears that socioeconomic inequality in obesity has almost disappeared. However, when depth and severity measures are considered, it is clear that the burden of obesity is still disproportionately borne by the poor. Appendix 1 displays the same information as Figure 1 for morbid obesity using a BMI threshold of 40. The trend is similar, but statistical power is lower as fewer individuals suffer from morbid obesity

4.2. Decomposition of the overall socioeconomic inequality in obesity

In what follows, we focus on the most recent 6 years of NHANES (2007–2012) and break down the FGT-CIs into factors that either makes a positive or negative contribution to the overall socioeconomic inequality. Table II presents the CI for each factor k , CI_k , which measures the extent of socioeconomic inequality in the factors themselves. Table II also shows the elasticity (or arc-elasticity for categorical factors) of the FGT obesity measure with respect to factor k , η_k , which quantifies to association between the factors and obesity. Finally, Table II displays the contribution made by factor k to the overall FGT-CI, CI_{Yk} . Figure 2 is a graphical

Table I. Trends in obesity and demographic and socioeconomic characteristics, 1971–2012

	NHANES I		NHANES II		NHANES III		Continuous NHANES			
	1971–1975		1976–1980		1990–1996		1999–2006		2007–2012	
	Mean	(SE)	Mean	(SE)	Mean	(SE)	Mean	(SE)	Mean	(SE)
BMI (kg/m ²)	25.2	(0.072)	24.8	(0.065)	26.4	(0.125)	28.2	(0.113)	28.7	(0.109)
Obesity (FGT measures)										
Status (or prevalence)	0.141	(0.005)	0.119	(0.004)	0.218	(0.008)	0.320	(0.008)	0.352	(0.007)
Depth	0.020	(0.001)	0.015	(0.001)	0.036	(0.002)	0.061	(0.002)	0.069	(0.002)
Severity	0.006	(0.001)	0.004	(0.000)	0.012	(0.001)	0.022	(0.001)	0.026	(0.001)
Age (years)	39.8	(0.217)	39.1	(0.213)	39.1	(0.249)	41.0	(0.241)	42.1	(0.304)
Female	0.543	(0.005)	0.508	(0.005)	0.512	(0.005)	0.500	(0.005)	0.503	(0.004)
Ethnicity/race										
Non-Hispanic white	0.844	(0.009)	0.827	(0.014)	0.755	(0.013)	0.703	(0.014)	0.671	(0.021)
Non-Hispanic black	0.104	(0.008)	0.098	(0.012)	0.111	(0.006)	0.111	(0.009)	0.115	(0.010)
Mexican American	0.024	(0.007)	0.027	(0.006)	0.054	(0.005)	0.079	(0.007)	0.086	(0.011)
other (including Hispanic)	0.027	(0.003)	0.047	(0.010)	0.080	(0.009)	0.106	(0.012)	0.127	(0.010)
Married	0.769	(0.007)	0.707	(0.009)	0.635	(0.011)	0.591	(0.010)	0.548	(0.010)
Not high school graduate	0.343	(0.012)	0.281	(0.009)	0.204	(0.010)	0.176	(0.007)	0.164	(0.008)
Non-US Born	0.067	(0.005)	0.069	(0.005)	0.136	(0.012)	0.157	(0.013)	0.177	(0.013)
Poor	0.107	(0.008)	0.104	(0.004)	0.128	(0.008)	0.133	(0.006)	0.163	(0.009)

SE, standard error; FGT, Foster–Greer–Thorbecke; NHANES, National Health and Nutrition Examination Survey

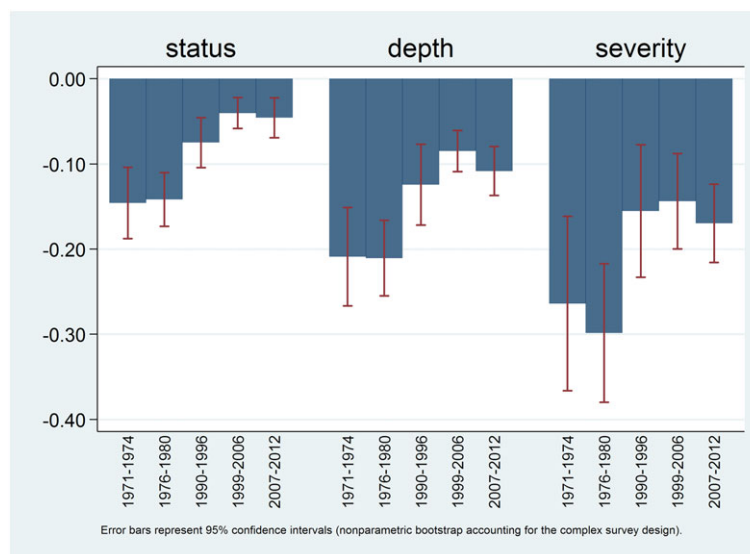


Figure 1. Trends in the concentration indices of status, depth, and severity of obesity in the United States, 1971–2012. [Colour figure can be viewed at wileyonlinelibrary.com]

depiction of the decomposition with positive contributions to the FGT-CI drawn upwards and negative contributions drawn downwards (Wagstaff et al. 2011).

The results show that the largest negative contributions to the overall FGT-CIs are the direct effect of income and education. The direct contribution of income can be further decomposed into the CI of income (0.319), multiplied by the elasticity of obesity with respect to income, which respectively amounts to -0.109 , -0.259 , and -0.428 for status, depth, and severity. Therefore the direct contribution of income to the FGT-CIs is negative and increases in magnitude as one progresses from status (-0.035), to depth (-0.083) and severity (-0.137). The overall contribution of education is negative as higher education is more concentrated among the rich, and obesity is negatively correlated with increasing education level. Race also makes a negative contribution to the FGT-CIs, as non-whites are more likely to be both poor and obese (with the exception of other races who are less likely to be obese, which cancels out the income effect).

On the other hand, immigrant status and age make a positive contribution to the FGT-CIs for all obesity measures. Immigrants are poorer than US-born respondents and slimmer, making the contribution of immigrant status to the overall FGT-CIs of obesity positive. Conversely, older adults are more likely to be richer and obese, which also results into a positive contribution to the FGT-CIs. Marital status is statistically significant and positive only for one obesity measure (status:0.011). Married adults tend to be richer, and on average, those who are married are more likely to be obese.

4.3. Decomposition of the socioeconomic inequality in obesity by race

Socioeconomic inequality with respect to obesity differs by races and ethnicities (refer to Figure 3 and Appendix 2). Whites exhibit the largest socioeconomic inequality with FGT-CIs that are negative and statistically significant for status (-0.049), depth (-0.119), and severity (-0.193). The largest contributors to the negative socioeconomic inequality for whites are income and education. The negative elasticity of obesity with respect to income increases in magnitude from status (-0.154) to depth (-0.334) and severity (-0.530), consequently increasing the contribution of income to the overall FGT-CIs of obesity from -0.042 for status to -0.090 and -0.143 for depth and severity. The decomposition also reveals that lower education is simultaneously associated with lower income and higher likelihood of being obese, accounting for -0.038 , -0.051 , and -0.070 of the overall FGT-CI of status, depth, and severity of obesity, respectively.

Table II. Decomposition of the FGT-CI of status, depth and severity of obesity, 2007–2012

Decomposition factor k	Status			Depth			Severity		
	CI_k	η_k	CI_{Yk}	η_k	CI_{Yk}	η_k	CI_{Yk}	η_k	CI_{Yk}
Age	0.042* (0.004)	0.446* (0.067)	0.019* (0.004)	0.482* (0.089)	0.020* (0.005)	0.504* (0.164)	0.021* (0.007)	0.504* (0.164)	0.021* (0.007)
Gender (reference: female)	0.024* (0.005)	-0.020 (0.016)	-0.000 (0.000)	-0.143* (0.021)	-0.003* (0.001)	-0.207* (0.035)	-0.005* (0.001)	-0.207* (0.035)	-0.005* (0.001)
Race (reference: non-Hispanic white)									
Mexican Hispanic	-0.374* (0.022)	0.034* (0.006)	-0.027* (0.005)	0.031* (0.008)	-0.033* (0.006)	0.027* (0.011)	-0.039* (0.009)	0.027* (0.011)	-0.039* (0.009)
Hispanic	-0.320* (0.026)	0.021* (0.005)	-0.013* (0.003)	0.024* (0.008)	-0.012* (0.003)	0.030* (0.012)	-0.010* (0.004)	0.030* (0.012)	-0.010* (0.004)
Other race	-0.022 (0.034)	-0.017* (0.008)	0.000 (0.001)	-0.017 (0.011)	-0.008* (0.003)	-0.018 (0.017)	0.000 (0.001)	-0.018 (0.017)	0.000 (0.001)
Education (reference: <9th grade)									
Some high school	-0.378* (0.024)	-0.006 (0.008)	-0.029* (0.008)	0.002 (0.015)	-0.043* (0.010)	0.022 (0.025)	-0.059* (0.015)	0.022 (0.025)	-0.059* (0.015)
High school graduate	-0.139* (0.017)	-0.000 (0.016)	0.000 (0.002)	0.015 (0.021)	-0.001 (0.006)	0.022 (0.033)	-0.008 (0.009)	0.022 (0.033)	-0.008 (0.009)
Some college	-0.009 (0.017)	0.014 (0.016)	-0.000 (0.000)	0.012 (0.027)	-0.002 (0.003)	0.019 (0.043)	-0.001 (0.001)	0.019 (0.043)	-0.001 (0.001)
≥college graduate	0.343* (0.014)	-0.091* (0.031)	-0.031* (0.011)	-0.116* (0.041)	-0.040* (0.014)	-0.137* (0.058)	-0.047* (0.020)	-0.137* (0.058)	-0.047* (0.020)
Marital status (reference: single)									
Married	0.152* (0.010)	0.087* (0.019)	0.011* (0.003)	0.029 (0.027)	0.007 (0.004)	-0.035 (0.048)	0.004 (0.005)	-0.035 (0.048)	0.004 (0.005)
Living with partner	-0.224* (0.034)	0.002 (0.005)	0.013* (0.003)	-0.009 (0.009)	0.004 (0.004)	-0.028 (0.014)	-0.005 (0.007)	-0.028 (0.014)	-0.005 (0.007)
Divorced	-0.103* (0.022)	0.014* (0.006)	-0.001 (0.001)	0.003 (0.008)	0.002 (0.002)	-0.010 (0.012)	0.006 (0.003)	-0.010 (0.012)	0.006 (0.003)
Separated	-0.350* (0.028)	-0.001 (0.002)	0.000 (0.001)	-0.002 (0.004)	-0.000 (0.001)	-0.002 (0.006)	0.001 (0.002)	-0.002 (0.006)	0.001 (0.002)
Widowed	-0.243* (0.045)	0.001 (0.002)	-0.000 (0.000)	-0.002 (0.002)	0.001 (0.000)	-0.006 (0.004)	0.002 (0.001)	-0.006 (0.004)	0.002 (0.001)
Immigration Status (reference: US born)	-0.207* (0.026)	-0.085* (0.014)	0.018* (0.004)	-0.144* (0.023)	0.030* (0.006)	-0.200* (0.033)	0.041* (0.009)	-0.200* (0.033)	0.041* (0.009)
Poverty income ratio	0.319* (0.007)	-0.109* (0.043)	-0.035* (0.014)	-0.259* (0.057)	-0.083* (0.018)	-0.428* (0.082)	-0.137* (0.026)	-0.428* (0.082)	-0.137* (0.026)
Residuals	—	—	-0.002 (0.003)	—	-0.004 (0.006)	—	0.003 (0.012)	—	0.003 (0.012)
Overall inequality	—	—	-0.046* (0.012)	—	-0.109* (0.014)	—	-0.170* (0.023)	—	-0.170* (0.023)

CI_k , concentration index of factor k ; η_k , elasticity of the FGT measure Y with respect to factor k ; CI_{Yk} , contribution made by factor k to the overall FGT-CI; FGT, Foster–Greer–Thorbecke; CI, concentration index.

*Statistically different from 0 at the 5% level (nonparametric bootstrapped standard errors in brackets).

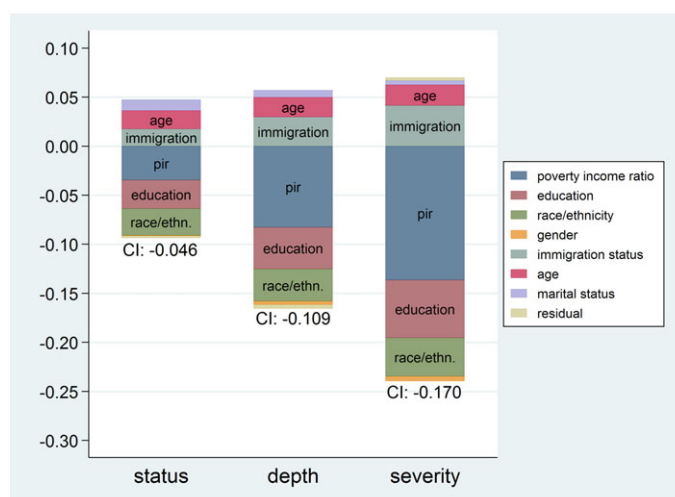


Figure 2. Decomposition of the Foster–Greer–Thorbecke-concentration index (CI) of status, depth, and severity of obesity, 2007–2012. [Colour figure can be viewed at wileyonlinelibrary.com]

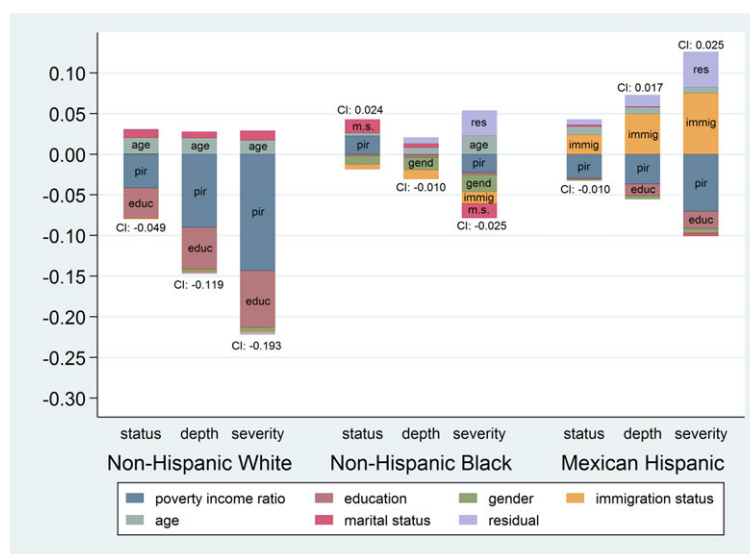


Figure 3. Race-specific decompositions of the Foster–Greer–Thorbecke-concentration index (CI) of status, depth, and severity of obesity, 2007–2012. [Colour figure can be viewed at wileyonlinelibrary.com]

Compared with whites, the socioeconomic inequality in obesity is much less marked for blacks. The overall FGT-CI for obesity status is slightly positive and statistically significant (0.024), while those for depth and severity are not statistically significant but suggest that the burden of obesity might still be disproportionately born by the poor. In stark contrast to the results from whites, the direct contribution of income to inequality in obesity is positive for status (0.023) and not statistically significant for depth and severity. As for education, it is found to make no direct contribution to the overall socioeconomic inequality of obesity.

Interestingly, no socioeconomic inequality in obesity was found for Mexican Hispanics; in fact, all FGT-CIs were positive but not statistically significant. What completely cancels out the cumulated negative effects of

income and education is the effect of immigrant status. The decomposition reveals a positive contribution to the overall FGT-CIs for immigrant status, amounting to 0.024, 0.050, and 0.075 for status, depth, and severity of obesity, respectively, which more than cancels out the cumulated negative effects of income and education. This positive contribution is a result of both the negative CI for immigrants and the negative arc-elasticities of all measures of obesity with respect to immigrant status. In other words, Mexican Hispanics that were born outside the United States are both poorer and thinner than their US-born counterparts, resulting in a positive association between body weight and income.

4.4. Decomposition of the socioeconomic inequality in obesity by gender

Figure 4 depicts the decomposition of the FGT-CIs separately by gender; the corresponding estimates can be found in Appendix 3. It can first be noticed that socioeconomic inequality is considerably less for men compared with women. The FGT-CIs for men range from 0.014 (not statistically significant) for obesity status to -0.093 for severity while they range from -0.101 to -0.203 for women.

The main driver of this difference is income. While the CI of income is about the same, the elasticity of obesity measures with respect to income is more negative among women for all three measures (it is even slightly positive for obesity status among men, but this is not statistically significant). In other words, the inverse association between income and obesity is stronger among women. Marital status also explains part of the difference in socioeconomic inequality in obesity between men and women. Marital status has a positive effect for men and no statistically significant effect for women. The CIs for marriage with respect to income amount to 0.128 for men and 0.175 for women; therefore, being married is associated with higher income, particularly for women. However, the difference between men and women predominantly lies in the association between being married and body weight. For women, the arc-elasticity of depth (not statistically significant) and severity of obesity with respect to being married is negative, which results in a negative association between income and obesity outcomes. On the other hand, association between body weight and being married is positive for men, and as a result, the contribution of marriage to the FGT-CI of obesity measures is positive.

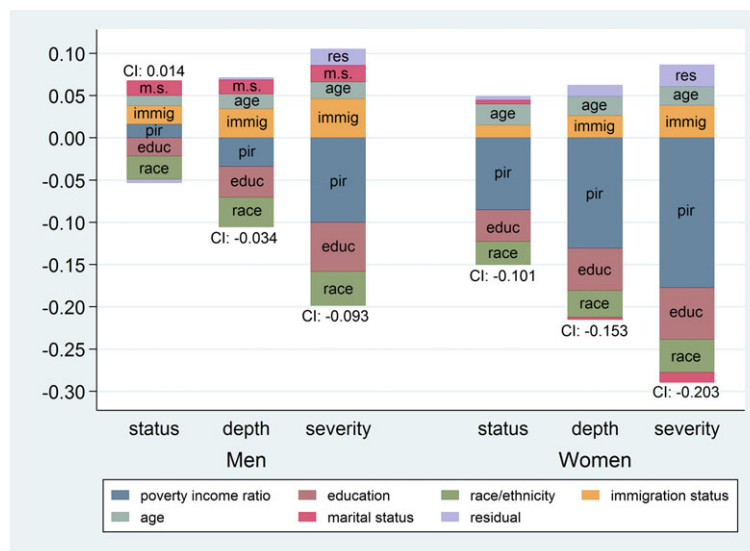


Figure 4. Gender-specific decompositions of the Foster–Greer–Thorbecke-concentration index (CI) of status, depth, and severity of obesity, 2007–2012. [Colour figure can be viewed at wileyonlinelibrary.com]

5. DISCUSSION

Our results show that socioeconomic inequality has decreased not only for obesity status but also for its depth and severity. Hence, the observed decrease is not merely a threshold effect with the rich catching up by crossing the threshold after the poor, but reflects a deeper change as the more severe cases of obesity are also obtaining more equally distributed according to income. A potential explanation for the decrease in socioeconomic inequality in obesity over the past decade is that the societal environment has become a more important contributing factor to the increase in obesity rates than individual characteristics. This is in line with recent studies that show that the neighborhood has an independent effect on long-term health outcomes (Ludwig et al. 2012) and that such neighborhood effects can outweigh that of individual income (Bilger and Carrieri 2013). The modern ‘obesogenic’ environment, with its low-cost, energy dense, mass-prepared food and greater portion sizes is likely to have contributed to a higher prevalence and severity of obesity across all income groups (Zhang and Wang 2004). On the other side of the energy expenditure-weight equation, physical activity has been declining over the same period. Technological progress and the reduction in jobs requiring manual labor has resulted in more sedentary lifestyles for all SES groups in the United States, also potentially contributing to lower socioeconomic inequality in obesity (Finkelstein et al. 2005). However, our study also reveals that even though it is decreasing, socioeconomic inequality in obesity is still sizeable when its severity is considered. Indeed, the FGT-CI for severity amounts to -0.170 in 2007–2012 and showed no evidence of decline since 1990. Thus, while socioeconomic inequality in status of obesity has almost disappeared, the depth and severity of obesity continues to disproportionately affect the poor.

The decomposition results show that the contributions of income and education to the overall FGT-CIs are both negative. In fact their cumulated contribution is even greater than the overall FGT-CIs with their effect partly compensated by age and immigrant status. These results provide further evidence of the existence of a negative socioeconomic inequality in the distribution of obesity.

Stratifying analyses by race reveals differences in socioeconomic inequality for whites, blacks and Mexican Hispanics. While this paper and earlier studies (e.g., Zhang and Wang 2004) show that, compared with Whites, minority groups have a lesser concentration of obesity among the poor, decomposing the FGT-CIs reveals that income still makes a negative contribution to the overall FGT-CIs. Decomposition results for Mexican Hispanics show that their statistically insignificant overall FGT-CIs are due to the strong relationship between being an immigrant and having both lower wages and lower body weight, which completely cancels out the negative contribution made by income. This finding is consistent with the literature on the health of US immigrants who have been found to have lower mortality rates and in particular to be less likely to be obese than native-born Americans (e.g., Cunningham et al. 2008). Without the decomposition analysis, one would have concluded that there is no negative socioeconomic inequality for Mexican Hispanics when in fact it is merely masked by the immigration effect.

Results stratified by gender reveal that socioeconomic inequality in obesity considerably differs between men and women. The smaller socioeconomic inequality for men may be partly explained by greater employment in manual labor among low income men, which is consistent with theories of income and obesity posited by Lakdawalla and Philipson (2009). An additional explanation is that women have been shown to be more affected by the negative societal attitude toward obesity (Puhl and Brownell 2001); therefore, they are more likely to invest resources in order to pursue a thinner ideal than men (Zhang and Wang 2004).

When interpreting the results, one should also always keep in mind that CIs are descriptive statistics. The question is not whether it is income that determines obesity outcomes or the opposite (both effects coexist) but to what extent income and obesity are associated to one another in order to describe the health condition of the poor compared with the rich. Similarly, the decomposition of the CI is not meant to reveal causal effects either but merely aims at revealing additional factors that are simultaneously correlated with income and obesity. Further, the CI cannot distinguish between a decrease in obesity among the poor, and an equivalent increase in obesity among the rich as both changes would make the CI increase in absolute terms. As the CI

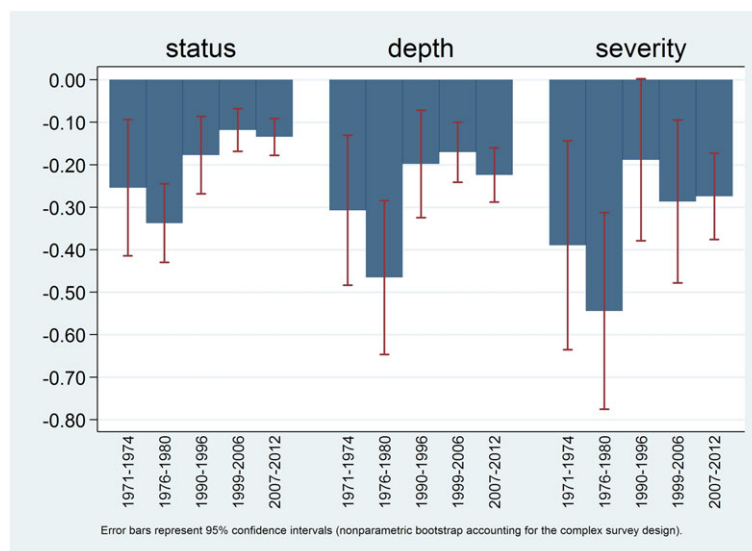
solely records the distribution of obesity, one needs to simultaneously analyze obesity trends to distinguish between the two alternative explanations.

A practical but important issue is whether or not to include PIR as a decomposition factor. Including the SES variable is consistent with the study, our method is based on Wagstaff *et al.* (2003) and is widely used in practice (e.g., O'Donnell *et al.* (2012); Van de Poel *et al.* 2007). However, not all researchers agree with this practice. For instance, Erreygers and Kessels (2013) find it unjustified on the grounds that this inclusion decreases the residual term without adding any explanative power to the decomposition. Notwithstanding, we chose to include PIR in the decomposition not only because it is a legitimate determinant of health but also because we see it important to control for PIR in the health regression when measuring the other factors' elasticities. We think that this approach is more consistent with the mechanics of the decomposition where the elasticities measure the correlations between health and its factors independently of income while the CIs capture the association between these factors and income. As for income, we interpret its contribution to the decomposition as its direct association with socioeconomic inequality after controlling for all other factors included. The magnitude of this contribution increases with income inequality as measured by the Gini index (i.e., the CI of income with respect to income) and the elasticity of obesity with respect to income.

A potential source of bias are missing values (e.g., Zhong 2009), which respectively amount to 8.96% and 4.01% for the PIR and BMI variables in the 2007–2012 NHANES sample. These values are not completely missing at random as those not reporting their income, on average, have a BMI 0.682 lower, are 1.32 years older, more likely to be Mexican Hispanic (+6.91%) or Hispanic (+6.80%) and less likely to have attended some college (−5.38%) or completed college (−8.36%). On the other hand, no statistically significant difference was found between those with missing and available BMI. Assuming that the data are missing at random, we multiply (20 times) imputed missing BMI and PIR values using Bayesian Markov Chain Monte Carlo data augmentation (e.g., Schafer 1997) while assuming an underlying multivariate normal model including all variables used in the analysis. Re-estimating the CIs and their decomposition after imputation showed little difference. All differences are below 0.01, and no interpretation is altered. Another limitation of our study is that the PIR variable is censored at five times the poverty line in continuous NHANES (19% of the sample). However, our results are robust to various imputation methods of the censored values. Last, within-family distribution issues are ignored because NHANES income is recorded at family level. It has, for instance, been shown that husband and wives do not fully pool their resources (Lundberg *et al.* 1997) and that intra-household bargaining power relates to wage rates (Pollak 2005). As income and wage rates (Weichselbaumer and Winter-Ebmer 2005) are on average lower among women, we likely underestimate income inequality between genders and, consequently, underestimate the negative contribution of gender to socioeconomic inequality in obesity.

Despite its dramatic decline since the 1970s, socioeconomic inequality in obesity is still a reality. The problem has now mostly shifted toward an increasing number of low income individuals who are severely obese and who are thus at a greater risk of suffering from the double burden of poverty and obesity-related health conditions. Obesity-reducing policies should thus be mindful of not further deteriorating the economic condition of the poor. Sin taxes such as linking the price of foods (Kim and Kawachi 2006) and beverages to their healthiness (e.g., Brownell and Frieden 2009; Finkelstein *et al.* 2013) should be levied with caution, and their potential regressivity be assessed alongside their effectiveness. The indirect approach of refocusing attention away from health care and health-related behaviors toward education and income recommended by Deaton (2002) is worthwhile considering. In particular, strengthening public education would likely have the double benefit of reducing economic inequalities and obesity. In order to successfully monitor the effect of such policies, policy makers need measures that make full use of the information that is available on the issue. By accounting for—instead of discarding—the information that lies beyond the obesity threshold, the FGT-CIs we propose are such measures. It is worth mentioning that our FGT-CIs are by no means limited to the study of obesity but could straightforwardly be applied to any quantitative variable defined above or below a threshold. There are numerous potential applications not only to other health-related variables such as blood pressure (hypertension) and blood sugar level (diabetes), which like obesity are key risk factors for major non-communicable diseases, but also to other fields of economics and beyond.

APPENDIX 1 TRENDS IN THE CONCENTRATION INDICES OF STATUS, DEPTH, AND SEVERITY OF MORBID OBESITY (BMI > 40) IN THE UNITED STATES, 1971–2012



CONFLICT OF INTEREST

The authors have no conflict of interest.

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